Medical Service Quality and Office Rent Premiums: Reputation Spillovers

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Abstract

Location spillovers are a common theme in real estate and urban economics research, but this is the first test on the relationship between hospital service quality and the demand for proximate medical office space. We hypothesize that hospitals with reputations for high quality service represent an opportunity for physicians, and other service providers, to benefit from reputation spillovers. Further, the reputation benefit is capitalized into the practices' willingness to pay for proximate office locations, thereby driving up the rental rates for nearby space. We find that distance from, and overall quality ranking of the hospital, both independent and in concert, are significantly linked to the base rents. The degradation in rent with distance is significantly greater when the hospital is ranked high in overall service quality, supporting the notion that a rent premium is linked to the high-quality hospital rather than simply an artifact of the neighborhood.

Keywords Medical office rents · Commercial property markets · Spillovers · Reputation effects

Introduction

Since the 1990s numerous studies have focused on the determinants of office rental rates (see, for example, Clapp, 1980, Glascock et al., 1990, Sivitanidou, 1995 and Bollinger et al., 1998). In many instances the research examines the influence of

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location amenities in determining rent differentials. Much of the work implicitly treats all office rental spaces as similar, and there has been little work in segmenting the office market according to tenant type. We refer specifically to the factors that influence rental rates for medical-specific office space, typically referred to as the medical office building (MOB). These properties have special design and location features (discussed below) that differentiate them from more homogeneous office space. There is a paucity of research on MOB due largely to the lack of available and accessible data (Wei, 2012 and Goodman & Smith, 2020 represent the few academic works).¹ Further, there has been little observed distinction in the literature on the tenants and space requirements for the MOB asset; thus, there has been little incentive to segment MOB from the larger office market.

The MOB is not an insignificant segment of the overall office market. Since 2015 MOB has attracted on average over \$11 billion dollars per year in investment with peak transaction volume in 2017 at \$14.5 billion (Revista, 2020). As healthcare delivery evolves, outpatient service space is expected to continue to grow. Since 2005 outpatient centers have grown over 66% to nearly 70,000 units (CBRE, 2018). The US demand for medical office space will continue to increase because during the next ten years, the 65-plus age cohort will grow by 17 million individuals (O'Hara & Caswell, 2013), accounting for over 20% of the population by 2030. While the non-elderly populace will grow at a more modest pace during the same period, ACA-induced Medicaid expansion, and the mandated utilization of insurance exchanges is expected to increase health care coverage by an additional 27 million people.

The office market over the past 20 years has seen extremely low cap rates through 2005–06 when credit and liquidity were extensive, the inverse in 2008–10 with the recession and evaporation of credit, and a moderate period since then with a stabilizing economy and relatively “cheap” money.² Because liquidity and credit availability are global factors, this cyclical trend has been national in scope rather than locally focused. With this growth comes an increased interest in performance measures for subsets of the office market, more specifically the medical office building market. Additionally, there has been increasing interest in subsets of the office market as institutional investors attempt to offset the volatility of office investments on an operating basis (i.e. sharp declines in net operating income during recessions) leading them to alternatives such as MOB that may exhibit more stability in the income profile.

Similarly, the literature on health service quality is expansive. However, few studies have observed links between service quality and profitability of hospitals or their affiliates. Adelino and Lewellen (2019) examines the relationship between financial constraints and health service quality standards. Their analysis tests whether hospitals shift towards more intensive and more profitable treatment options as a result of a financial shock, such as the financial crisis. They conclude that for the sample of nonprofit hospitals they observed, the organizational form combined with the hospitals' internal governance structures shield patients from undesirable shifts in quality in response to financial shocks.

¹ There are a number of professional reports that are produced by CBRE, Marcus & Millichap that focus on the MOB market, and most of these have only recently been offered.

² At the time of this writing (February 2021), Covid-19's impact on the real estate markets including the MOB is as yet uncertain.

In the following analysis we seek to measure spillover effects from hospital service quality ratings. Such location amenities are a common theme in real estate and urban economics research, yet no such test has been done on hospital reputation and the demand by providers for proximate office space. Relying on secondary data from the CoStar Group (CoStar) and public sources in developing the models, our results indicate that although the real estate capital markets are international in scope, the local space market still prevails in the pricing of real property assets. As anticipated, base rents decrease as the distance from a hospital increases and, measures of quality are capitalized into the willingness to pay of tenants. Tenants appear to pay premiums for locations near hospitals with higher quality ratings. We hypothesize that hospitals with strong reputations for high-quality service (provided in part by high-quality affiliated physicians) will represent an opportunity for physicians (broadly referred to as providers) to benefit in the form of a reputation spillover, thereby increasing potential revenue.³ Further, this increase in potential revenue is capitalized into the practices' willingness to pay for proximate office locations, thereby driving the rental rates for nearby space.

In the remainder of this article we provide support for segmenting medical office markets from the more general professional office sphere, and we briefly review the literature on office rent determinants. We then provide a conceptual model that the provider (potential tenant) faces when considering space in a metropolitan area. Description of the data and the analysis follow along with the results obtained from the models. The conclusion summarizes the outcomes and the implications from the analysis.

Determinants of Office Rents

Research on office rent determinants can be practically allocated into property-specific and geospatial categories. Property-specific research focuses on the price elasticity of rent as a function of vacancy, temporal changes in demand for space and the physical characteristics of the property. Hekman (1985), Shilling et al. (1987), Pollakowski et al. (1992), Hendershott (1996), Hendershott et al. (2002) all find an empirical connection between vacancy and rents in office markets. Frew and Jud (1988), Wheaton and Torto (1989) and Sivitanides (1997) also studied the impact of vacancy rates on office rents. Wheaton and Torto (1994) utilize office rent indices to document the persistence of a rent/vacancy relationship and Slade (2000) examines the variation in market participants' value of office space amenities during different periods in a market cycle. Clapp (1980) identifies property age as a physical characteristic, along with other locational variables, as significant factors that influence the level of office rents.

Additional research verifies the significance of property age, including that of Bollinger et al. (1998), and Slade (2000). In the early-1980s, Brennan et al. (1984) identify building size and locational characteristics within the CBD as key factors, and then Chuangdumrongsomsuk and Fuerst (2017) develop a model of rent determinants

³ We will often use the term "provider" rather than physician, because the modern health provider setting may offer nurses, nurse practitioners, technicians, laboratory personnel and support staff, all of whom provide health care services.

between suburban and CBD space. Hough and Kratz (1983), Vandell and Lane (1989), Doiron et al. (1992) and Robinson et al. (2017) investigated the impact of structural features on rent, and Colwell and Ebrahim (1997) provided a framework for determining the optimal design of an office building. Sivitanidou (1995) and Hui and Liang (2016) show that spatial amenities influence office rents. Glascock, Jahanian and Sirmans (1990) analyzed office rents across different classes of buildings, while Shilton and Zaccaria (1994) provide evidence that office values are a function of building size. There is also an expanding literature on the impacts of “green” design and amenities on rents (see Wiley et al., 2010, Eicholtz, Kok and Quigley, 2010 and Devine & Kok, 2015 for examples).

Research addressing geospatial issues focuses on the broader office market, the role of location within a market and spillover impacts from proximate properties. Colwell and Sirmans (1978); Colwell (1980), Colwell and Munneke (1997); Colwell (1999) and Savini and Aalbers (2016) have examined the structure of urban land prices, illustrating how rents vary depending on a property’s distance to the city center. Archer and Smith (1994), find that downtown office properties play a significant role in local economies and that the future of the central business district as a core node in urban space did not appear to be ending soon (as of the early 1990s). Along this same line, Shilton and Stanley (1999) found a high concentration of Fortune 500 firms in the largest metropolitan cities, although technological changes suggest that firms could reduce costs by migrating away from high-cost city centers. Bollinger et al. (1998) and Albouy and Lue (2015) investigated how locational differences in wage rates, transportation rates and the concentration of support services affect the spatial variation in office rents, and they find that these items do contribute to an estimate of rental rates. Our work intersects both threads of the literature on office-property research with a focus on the potential for geospatial spillovers. It extends the understanding of the factors that impact office rents by providing evidence in support of a rationale for distinguishing between professional and medical office space.

Segmenting Office Markets

Medical office buildings (MOB) are constructed or converted for medical use primarily for office visits, laboratory tests, and outpatient services. Examples include physician office buildings, ambulatory care facilities, surgery centers, as well as medical imaging, health services administration, therapy (physical and psychological), and wellness centers. Like professional office buildings, utility and pricing for these spaces is typically measured in square feet (Wei, 2012). MOB are developed and operated by hospitals or health systems, physician practice groups, and third party private/institutional investors and managers. The U.S. MOB real estate market is a substantial segment of the total office market, and accounts for roughly 62% of all medical facility space or roughly 4.5 square feet per insured person in the United States (Alexander, 2015).

Numerous market characteristics serve to separate MOB from other professional office space (POB). Medical office tenants and physician practices typically have longer tenure and relocate less frequently than general office tenants. Seemingly offsetting this, the competition for new patients is also steering health service providers

to more off-campus sites such as community retail centers that are viewed as more convenient or accessible. This “*retailization*” of healthcare is evident in the increased development of smaller suburban medical office spaces and urgent care clinics. In addition to specific buildout directives, medical tenants frequently rely on potentially hazardous or sensitive materials (e.g. radiation from oncology treatments and scanners, medically sensitive waste such as used needles) that require specific structural components such as lead lined walls, and dedicated disposal. Many health services tenants such as urgent care, x-ray and MRI scans, and lab diagnostics conduct business during evenings and over weekends. Medical tenants typically face greater compliance review for accessibility with the Americans with Disabilities Act. Patient privacy issues (including the need for multiple waiting rooms) can create special circumstances with respect to common entry and landlord access.

Physicians historically represented a cottage industry of small or solo practices. The majority of the over 970,000 doctors and residents in the United States still work mainly from smaller, office-based practices. However, over the last two decades, providers have changed their organization forms; many have merged their offices into larger practices. Others have sold practices to health care conglomerates, insurance companies, and physician management firms. Still others have contracted to provide exclusive services to providers such as hospitals and some have gone to work for larger providers as salaried employees (Kirchhoff, 2013). The provider experience is part of a broader trend toward consolidation in health care, due in part, to the increased costs of administrative compliance required under the Affordable Care Act.

Consolidation can create economies of scale for healthcare providers which can include shared fixed costs (including electronic medical records), specialization of labor inputs (e.g., use of non-physician personnel), internalization of referrals, exploitation of reputational economies, bulk purchasing, use of internal quality monitoring, and extended patient coverage. At the same time, providers may suffer from inefficient scale (number of physicians, use of non-physicians, and ancillary services), scale diseconomies due to free-riding on colleagues within a group setting, higher patient travel costs, excessive use of inputs, excessive administrative costs, and failure to use a cost-minimizing mix of inputs and outputs (Pope & Burge, 1996, Casalino et al., 2003, Sarma et al., 2010, Burns et al., 2014). As the consolidation activity continues, lawmakers have watched closely to ensure that further concentration does not result in negative impacts in terms of reduced consumer access, higher prices, or compromised quality of service, through a loss of competition (Bloom et al., 2015).

One potentially large and positive outgrowth of physician practice consolidation is the added value created from knowledge and reputation spillovers within the larger practice and across multiple practices (horizontal) and, between physicians and hospitals (vertical). The literature on both knowledge and reputation spillovers indicates the importance of proximity as a key factor in the pace and breadth of these benefit transfers (Baicker & Chandra, 2010). We seek to identify such reputation alliances in the health services market. If the hospital reputation is important in physicians’ deciding where to position their practices, one would expect a higher willingness to pay for office space proximate to hospitals with higher rather than lower ratings.⁴

⁴ Not all physician specialists require proximity to the hospital to carry out their practices (e.g. dermatology, or general practitioner), so this directive is a generalization across all disciplines demanding MOB space.

Folland et al., 2018, (p. 259) discuss how hospital quality rankings stack up against patient outcomes, citing a study by White et al. (2014) on relationships between hospital prices, various quality indicators and other hospital characteristics. Hospitals with higher price structures are, on average, much larger than low-price hospitals, and have larger market shares. Further, although the more expensive hospitals outperformed the lower-priced hospitals on *U.S. News & World Report* ratings (there are no low-price hospitals on the list), they generally performed the same or worse on most objective quality indicators (e.g., postsurgical death rates and serious blood clots among surgical discharges).

Conceptual Model

To provide a conceptual framework for the empirical analysis we rely on a model used in studies of professional firm location. Early versions of these models (Bollinger et al., 1998 and Clapp, 1980) indicate that the ability to meet face to face with suppliers and customers is an important factor in the location decision. Our adaptation assumes that health care providers' practices, much like other professional firms, search the metropolitan area for the location that maximizes profit, given the set of amenities available at that location including proximity to additional services that are demanded by their clients/patients and the ability of clients to access the location. As such all providers and provider groups face the following production function:

$$Q = f(OS, K, N, PA, HS, HQ) \quad (1)$$

where, Q = output of medical services; OS = office space; K = derived utility from depreciable capital either acquired or contracted via the hospital or other provider; N = measure of labor input efficiency; PA = patient access to location; HS = contractual services facilitated by proximity to the hospital or other third-party provider; and HQ = hospital quality. Patient access is included as an input to represent the fact that medical services are provided in unique combinations depending on the individual client/patient. For a practice to be profitable, the location of the office should be proximate and accessible to a sufficient client base. This is one reason for the *retailization* of health services (i.e. "quick med" facilities and medical clinics in retail strip centers) that is a growing trend in the industry. Including the hospital services reflects the potential for economies of scale and agglomeration benefits, as well as the availability, if needed, of inpatient healthcare services, closer to the hospital.

Similarly, our focus on hospital quality is based on the notion that provider profitability is enhanced when aligned with a hospital that has a reputation for high quality service. Of course, the location of high-quality providers and hospitals is jointly defined as the potential benefits are bilateral; reputable providers will enhance the reputation of the hospital that they serve. This is similar to the case with the academic profession. Highly respected research academics gravitate to highly ranked universities and perpetuate and/or enhance the strong reputation.

Labor enters the production function of physician practices measured in efficiency units. Efficiency units increase as the distance between the practice and the hospital decreases such that

$$N = a(\bar{x})L \quad (2)$$

where a represents efficiency, L is labor hours and $(\bar{x})$ is the average distance to supporting medical facilities. Formulating labor in this manner captures the knowledge and technology exchange that come from both formal and informal interactions between employees in the practice, the hospital and other practices. The concept that physical location and proximity influences labor productivity has a strong presence in the literature both theoretically (Glaeser, 1994) and empirically (Ciccone and Hall, 1996).

With eq. (1) we can construct the cost and profit functions for physician office space as the following:

$$C = sOS(jHQ) + cK + eN + tuPA + tvHS, \quad (3)$$

$$\pi = PQ - C, \quad (4)$$

where, s represents the unit costs for MOB space, j is the anticipated premium to MOB space cost based on the reputation of the hospital, and c the cost of capital services. P is the reimbursement for provided medical services e , the cost per unit of labor efficiency, t , travel costs, and u and v represent distance for customers (patients) and suppliers (hospital).

Assuming the demand for medical services and input prices vary spatially, there are unique demand equations for each of the variable inputs. The demand equation for MOB space (OS), at location i is expressed as follows:

$$OS_i = f(s_i, j_i, c_i, e_i, t, u_i, v_i, w_i, x_i, R_i) \quad (5)$$

where w_i is the wage rate, x_i represents additional control variables in the demand for MOB space and R_i is expected revenue. It is hypothesized that the quality or reputation of the hospital creates a spillover effect that will enhance the earning potential of providers. This increased earning potential is capitalized into a rent premium for proximate office space. We will use the relationships from eqs. (1) through (5) to estimate a hedonic rent regression, explaining MOB rent per square foot, concentrating on the distance and quality impacts. We discuss the estimation methods after looking briefly at the underlying database.

Data and Variables

The principal data are drawn from commercial office base rental offerings from CoStar, made available through an academic license agreement. The observations are limited to 12 Metropolitan Statistical Areas in the United States, containing 124 counties. The current sample is driven by data access constraints but remains sufficiently diverse to provide confidence in the external validity of the results. The base rental data represents

a snapshot of asking rents from June 2015. With preliminary cleaning, the data consist of approximately 16,000 observed sites.⁵ A valid case can be made that there is variation between the observed base rent and the effective rent that is ultimately derived out of a lease negotiation. However, prior research by Mills (1992) and Slade (1997) provide support for relying on the base rent as a proxy for the effective rent.⁶

Table 1 presents the names, descriptions and summary statistics for the variables in the analysis. The dependent variable is the natural log of the base rent, *logrent*. The mean and median asking rent for the entire sample are around \$16.00 per square foot. The two variables central to the analysis are 1) the straight-line distance between the office and the hospital measured in meters and 2) the quality rating assigned to the hospital by the Centers for Medicare and Medicaid Services and provided in their Hospital Compare Database (CMS). Distance to the nearest health facility is represented by three different variables; the natural log of the distance in meters (*Indist1*), the measured distance in 1000's of meters (*distance*) and *distancesqrd*. Either the natural log, or inclusion of the distance-squared variable represents the expectation that the influence of distance from the hospital will decrease as one moves further away. The median distance from the nearest facility is around 3800 m and ranges from adjacent to 46,000 m.

As a robustness check, the analysis will include estimates with both the nearest and second nearest hospital included as right-hand side variables. The rationale for including the second hospital is that there are instances where the MOB is positioned in close proximity to more than one central health service facility and the base rent is actually a representation of the spillovers from multiple facilities. The variable *Indist2* represents the distance to the second nearest facility. Alternatively, if the nearest hospital is closer to the metropolitan center, our measured distance may simply be reflecting a metropolitan rent gradient; inclusion of a second hospital mitigates this possibility. In a third derivation of distance we convert distance into a series of bands. The bands are based on straight-line distance in 1000-m increments (e.g. band 1 is 0 to 1000 m, band 5 is 4000.01 and above etc.).⁷ Additionally, we will run the models with interactions between the distance variables and the indicator variable for MOB space (discussed below) to observe the impact that distance has on properties identified as MOB specific.⁸

⁵ The original dataset obtained from CoStar included approximately 19,500 observations. Roughly 615 proposed properties were removed, restricting the analysis to existing facilities. There were 1419 observations missing the year built that were removed. 199 did not have the number of stories listed, and 648 did not have the indication of base rent type (e.g. gross, net triple-net, modified). There were also 612 identified as mixed use (office with apartments or retail). These were eliminated in order to focus exclusively on the office market.

⁶ There is potential for bias in the CoStar data with respect to the represented sample identified as MOB properties. For example, many large health care systems have developed multi-function high quality facilities in affluent areas. These are typically leased exclusively to one health care system and will not be listed on CoStar. To the extent that they reflect proximity to desired location, their omission biases results against our findings. Additionally, some offices that house suppliers to the healthcare industry are listed in CoStar as MOB properties.

⁷ There is a valid case for creating distance bands based on travel time and we acknowledge the potential value in using such an approach. However, with over 70% of the entire observation set within 6000 m the difference between a travel and circular approach is likely trivial.

⁸ It should be noted that buildings proximate to a hospital will likely be attractive to medical professionals and health services support and thus compete in a premium rent market, even though they are not coded as medical in the CoStar database.

Table 1 Variable Dictionary and Summary Statistics

Variable	Description	Mean	Median	Std Dev	Min	Max
logrent	log of annual square foot base rent	2.754	2.773	0.374	0.000	4.420
rent	base asking rent	16,804	16,000	6,298	1,000	83,080
lndistl	natural log of nearest hospital distance	8.065	8.238	1.010	3.021	10.750
distance	meters to nearest hospital in 1,000 s	4.728	3.783	3.957	0.021	46.626
distancesqrd	meters squared distance to nearest facility in 1,000 s	38.009	14,312	77,180	0.000	2173.956
overall	overall hospital quality rating	3.315	3.000	1.088	1.000	5.000
distband1	0–1000 m distance from health facility	0.134	0.000	0.340	0.000	1.000
distband2	1001–2000 m distance band	0.143	0.000	0.350	0.000	1.000
distband3	2001–3000 m distance band	0.129	0.000	0.336	0.000	1.000
distband4	3001–4000 m distance	0.118	0.000	0.322	0.000	1.000
distband5	4001+ above meter distance band	0.476	0.000	0.499	0.000	1.000
ovlduml	hospital quality rank =1	0.035	0.000	0.184	0.000	1.000
ovldum2	hospital quality rank =2	0.238	0.000	0.426	0.000	1.000
ovldum3	hospital quality rank =3	0.246	0.000	0.431	0.000	1.000
ovldum4	hospital quality rank =4	0.340	0.000	0.474	0.000	1.000
ovldum5	hospital quality rank =5	0.141	0.000	0.348	0.000	1.000
lndist2	natural log of 2nd nearest health facility distance	8.929	9.058	0.774	3.761	11.363
olver45	coded 1 if the nearest health facility rank is 4 or 5	0.481	0.000	0.500	0.000	1.000
o2ver45	coded 1 if the 2nd nearest health facility rank is 4 or 5	0.471	0.000	0.499	0.000	1.000
class_c	classified as class C	0.336	0.000	0.472	0.000	1.000
class_b	classified as class B	0.555	1.000	0.497	0.000	1.000
class_a	classified as class A	0.109	0.000	0.311	0.000	1.000
medical	coded 1 if medical space	0.167	0.000	0.373	0.000	1.000

Table 1 (continued)

Variable	Description	Mean	Median	Std Dev	Min	Max
gross	gross lease quote	0.374	0.000	0.484	0.000	1.000
net	net lease quote	0.099	0.000	0.299	0.000	1.000
modified	modified lease quote	0.222	0.000	0.415	0.000	1.000
triple_net	triple net lease quote	0.258	0.000	0.437	0.000	1.000
stars	CoStar star rating	2.588	3.000	0.732	1.000	5.000
stories	number of stories	3.156	2.000	4.723	1.000	76.000
neighbor7	average rent of nearest 7 observations	16.863	16.040	4.634	5.897	48.226
fipsunemp	county unemployment rate when data was gathered	6.166	6.100	1.128	3.500	13.500
medicare_expend	annual medicare expenditures by county in millions	966.460	690.000	885.000	16.000	3100.000
constate	office located in a state with CON legislation	0.497	0.000	0.500	0.000	1.000

This table presents the variable descriptions and summary statistics. The data for the individual observations including property characteristics and rent structure are provided by the CoStar Group, Inc. The remaining variables (unemployment, Medicare expenditures, Certificate of Need state) have been gleaned from publicly available datasets

The second variable of interest is the proxy for perceived quality/reputation rating from CMS. The CMS data provides ratings of hospitals based on their compliance with various processes of care. The composite rating, *overall*, provided by CMS is an aggregate of the performance ratings for specified procedures (e.g. imaging, heart catheterization etc.). Ranging from 1 to 5, the rating provides a basis for ranking hospitals across multiple dimensions on consistency of care.⁹ There are two derivations in the quality variable that are employed in the models. We convert the rankings into five dummy variables (*overdum1–5*); and in order to include rank in an interaction with medical and distance we convert the rank into a single dichotomous variable coded 1 if the rank is 4 or 5, otherwise 0. This cutoff is based on information contained in the CMS dataset that indicates that the distinction between a rank of 4 and 5 is subjective and often driven by the reviewer's nuanced interpretation of available data. We also use quality rankings for the second nearest facility where appropriate in the models that follow.

CoStar also provides the property-specific control variables utilized in the models. These include the dichotomous variables indicating the assigned class of the office building (A, B, or C), the quoted rental type (gross, modified, net, and triple net), the number of stories, the year the structure was constructed, the location, and if the property is designated as medical. The year built is converted to an age variable and we include age squared due to prior research that indicates a declining rate of depreciation as the property ages (Fisher et al., 2005). Class B structures account for over 55% of the observations. Seventeen percent of the sample is designated as a MOB. The gross lease designation accounts for 37% of the office space observed. CoStar also reports the number of stories in the structure, ranging from 1 to 76 with the median at 2. CoStar also reports a subjective condition or overall quality and condition ranking in the form of a five-star (lowest = 1; highest = 5) rating system.¹⁰

We find that in most of our metropolitan markets medical office space rents for a premium over the more general professional office space.¹¹ To control for this premium, and to examine the differential relationships between distance and facility rank we include a dichotomous variable coded 1 if the CoStar data indicates the observed space is principally for medical use; otherwise it is 0. The modeling will be run on the entire dataset, as it is expected the hospital reputation will spill over to both MOB and POB, and incorporate interactions between measures of distance and rank with MOB.

The modeling includes local economic and health-oriented controls beyond those available in the CoStar data. There are numerous counties and neighborhoods within each of the markets and each county has its own unique influence on office rents. The county level unemployment rate (*fipsunemp*) serves as a control for, then current, local economic conditions. To account for the impact of the micro market, or neighborhood on rental rates, we calculate a variable representing the median quoted base rent from

⁹ We have also tested individual quality indicators separately. They tend to move together, leading to multicollinearity issues. One might interpret the summary composite as similar (although not identical) to one derived through factor analysis of multiple attributes.

¹⁰ CoStar evaluates and rates properties using a five Star scale based on the characteristics of each property type, including: architectural attributes, structural and systems specifications, amenities, site and landscaping treatments, third party certifications, and detailed property type specifics.

¹¹ This premium is due, in part to a higher cost per square foot for finish with more plumbing, electrical capacity and other base building enhancements (partitioning) frequently required in MOB space.

CoStar for the seven nearest neighbors based on the great circle distance (*neighrent7*). At the county level, we include the variable *medicare_expend*. This variable represents the annual spending, in millions of dollars, for Medicare reimbursed medical expenses at the county level. The data for this variable comes from CMS and the variable serves as a proxy for health care spending in the county.

We also control for a healthcare-specific public policy constraint referred to as the “Certificate of Need” or CON. State-level CON regulations impose restrictions on investments in medical infrastructure (i.e., buildings) and “big ticket” technology. The goals of CON are to reduce the costs associated with an oversupply of health services, and to ensure quality care. By extension, this premium represents a distortion in the market that constrains the expansion of medical services.¹² Goodman and Smith (2020) observe that MOB locations in states with CON legislation (35 states maintain have CON legislation as standing policy) have higher than average rent premiums over POB after controlling for the property and location factors. The variable is *constate* and it is interacted with the medical indicator variable to control for the influences that CON legislation has on property identified as suitable for medical occupancy.

Table 2, Panels A and B, segment the mean, standard deviation and sample size by MSA. Several variables have similar values across many, if not all, of the MSAs. For example, the average number of stars applied by CoStar sits around 2.50–3.00. The majority of properties are classified as class B in all observed MSAs with the minority in class A. There are also some important differences. The variable *medical*, which measures the proportion of observations in the MSA classified as medical, ranges from 9% in Boston and Pittsburgh, to 25% in Phoenix. The markets also vary widely in how leases are structured (gross, net, triple net, and modified) with *gross* dominating Denver and *triple net* representing over half the observations in Seattle. Such variation illustrates how norms for lease structure differ extensively across markets. Not surprising, there is also significant variation in the observed rental rates between MSAs. The mean observed rent in Minneapolis is \$13.78 and in Seattle the median is \$20.14. Interestingly, that variation is reduced in the variable *neighrent7*. Recall, this variable is mean base rent for the seven nearest neighbors for each observation. This variable provides a control for the influence of localized markets on the observed base rent, and what is observed in this table is the average value of that variable by MSA. Orlando has the lowest average at \$14.22 and Seattle is, again, at the top, with \$19.75. A quick review of the overall hospital ranking indicates a relatively minor difference across the MSAs. The variations in quality between MSAs is more prominently expressed in a review of the overall dummy variables representing the 1 to 5 rank scores. For example, in Atlanta 49% of the hospitals are ranked grades 1 or 2, while in Indianapolis there are no hospitals ranked below 3. In Denver 76% of the hospitals are ranked 4 or above and in Orlando only 25% are ranked 4 or 5.

We next summarize the foundational relationship between MOB and POB rents in the sample, comparing the mean rents for MOB and POB and comparing the MOB between states with Certificate of Need legislation and those without. This summary illustrates the average premium on base rents for MOB locations across the entire sample

¹² Goodman and Smith (2020) provide a detailed discussion of CON. The regulation (still active in 35 states) emerged from a belief that providers would pass along the higher capital costs to consumers and insurers in the form of higher prices.

Table 2 Summary Statistics Segmented across MSAs

Panel (a)									
MSA	Atlanta	Boston	Charlotte	Denver	Houston	Indianapolis			
Obs	2673	1659	1086	1404	1166	786	Mean	Std. Dev.	Std. Dev.
Variable	Mean	Mean	Mean	Mean	Mean	Mean			
logrent	2.644	2.755	2.733	2.805	2.912	2.601	0.308	0.379	0.379
rent	15.009	17.215	16.536	17.599	19.240	14.347	5.685	1.078	0.897
Indist1	8.326	8.167	7.979	8.030	7.896	7.959	3.636	1.078	0.897
distance	6.086	5.219	4.358	4.080	4.134	4.027	3.636	1.078	0.897
distancesqr	56.922	46.157	33.035	24.750	30.299	29.437	83.635	0.499	0.499
o1verall	2.774	3.312	3.329	3.952	3.377	3.817	1.231	0.499	0.499
distband1	0.115	0.130	0.146	0.096	0.170	0.116	0.376	0.499	0.499
distband2	0.100	0.137	0.152	0.155	0.156	0.167	0.363	0.499	0.499
distband3	0.092	0.115	0.113	0.178	0.124	0.201	0.330	0.499	0.499
distband4	0.091	0.085	0.146	0.150	0.111	0.127	0.315	0.499	0.499
distband5	0.602	0.533	0.442	0.421	0.439	0.392	0.496	0.499	0.499
ov1dum1	0.140	0.347	0.042	0.000	0.030	0.000	0.171	0.499	0.499
ov1dum2	0.345	0.476	0.300	0.067	0.290	0.000	0.454	0.499	0.499
ov1dum3	0.222	0.416	0.078	0.175	0.212	0.429	0.409	0.499	0.499
ov1dum4	0.189	0.391	0.445	0.498	0.209	0.326	0.407	0.499	0.499
ov1dum5	0.105	0.306	0.134	0.261	0.259	0.246	0.438	0.499	0.499
Indist2	9.196	8.982	9.203	8.794	8.481	8.733	0.744	0.499	0.499
o1ver45	0.293	0.455	0.579	0.759	0.468	0.571	0.499	0.499	0.499
o2ver45	0.286	0.452	0.550	0.607	0.503	0.643	0.500	0.499	0.499
class_c	0.336	0.473	0.325	0.214	0.273	0.377	0.446	0.499	0.499
class_b	0.533	0.499	0.522	0.669	0.563	0.519	0.496	0.499	0.499
class_a	0.131	0.337	0.153	0.116	0.164	0.104	0.370	0.499	0.499
medical	0.162	0.368	0.200	0.122	0.197	0.156	0.398	0.499	0.499
gross	0.386	0.487	0.411	0.473	0.442	0.408	0.497	0.499	0.499
net	0.073	0.261	0.066	0.020	0.047	0.123	0.212	0.499	0.499

Table 2 (continued)

modified	0.318	0.466	0.209	0.407	0.268	0.443	0.103	0.303	0.099	0.299	0.243	0.429
triple_net	0.187	0.390	0.238	0.426	0.183	0.387	0.359	0.480	0.364	0.481	0.165	0.372
stars	2.575	0.771	2.482	0.650	2.650	0.807	2.672	0.738	2.770	0.790	2.370	0.661
stories	3.129	4.824	2.917	1.954	2.743	4.379	3.928	5.208	5.000	7.867	2.762	3.831
neighrent7	16.704	4.066	15.018	4.024	16.192	5.496	17.343	6.071	17.715	4.549	18.872	3.575
fipsuncmp	6.926	0.979	5.654	0.996	6.346	0.394	5.687	0.518	5.148	0.244	6.422	1.099
medicare_expend	405.192	209.597	1118.999	495.222	482.075	252.355	273.537	75.785	2551.379	1087.296	643.716	401.943
constate	1.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel (b)												
MSA	Minneapolis	Orlando	Phoenix	Pittsburgh	Seattle	Sacramento						
Obs	1212	1240	1495	591	1301	1398						
Variable	Mean	Mean	Mean	Mean	Mean	Mean						
logrent	2.644	0.365	2.755	0.417	2.733	0.397	2.805	0.354	2.912	0.308	2.601	0.379
rent	15.009	5.469	17.215	8.125	16.536	6.092	17.599	6.639	19.240	5.685	14.347	4.811
Indist1	8.326	1.043	8.167	0.987	7.979	1.019	8.030	0.850	7.896	1.078	7.959	0.897
distance	6.086	4.460	5.219	4.351	4.358	3.749	4.080	2.848	4.134	3.636	4.027	3.638
distancesqr	56.922	78.745	46.157	80.805	33.035	78.002	24.750	36.822	30.299	83.635	29.437	88.516
o1verall	2.774	1.208	3.312	0.981	3.329	1.160	3.952	0.837	3.377	1.231	3.817	0.801
distband1	0.115	0.319	0.130	0.337	0.146	0.354	0.096	0.295	0.170	0.376	0.116	0.320
distband2	0.100	0.299	0.137	0.344	0.152	0.359	0.155	0.362	0.156	0.363	0.167	0.373
distband3	0.092	0.290	0.115	0.319	0.113	0.317	0.178	0.383	0.124	0.330	0.201	0.401
distband4	0.091	0.288	0.085	0.279	0.146	0.354	0.150	0.357	0.111	0.315	0.127	0.333
distband5	0.602	0.490	0.533	0.499	0.442	0.497	0.421	0.494	0.439	0.496	0.392	0.488
ov1dum1	0.140	0.347	0.007	0.085	0.042	0.201	0.000	0.000	0.030	0.171	0.000	0.000
ov1dum2	0.345	0.476	0.207	0.406	0.300	0.459	0.067	0.250	0.290	0.454	0.000	0.000

Table 2 (continued)

ov1dum3	0.222	0.416	0.397	0.489	0.078	0.269	0.175	0.380	0.212	0.409	0.429	0.495
ov1dum4	0.189	0.391	0.244	0.430	0.445	0.497	0.498	0.500	0.209	0.407	0.326	0.469
ov1dum5	0.105	0.306	0.145	0.352	0.134	0.341	0.261	0.439	0.259	0.438	0.246	0.431
Indis2	9.196	0.741	8.982	0.760	9.203	0.733	8.794	0.680	8.481	0.744	8.733	0.804
o1ver45	0.293	0.455	0.389	0.488	0.579	0.494	0.759	0.428	0.468	0.499	0.571	0.495
o2ver45	0.286	0.452	0.460	0.499	0.550	0.498	0.607	0.489	0.503	0.500	0.643	0.479
class_c	0.336	0.473	0.444	0.497	0.325	0.469	0.214	0.411	0.273	0.446	0.377	0.485
class_b	0.533	0.499	0.482	0.500	0.522	0.500	0.669	0.471	0.563	0.496	0.519	0.500
class_a	0.131	0.337	0.074	0.262	0.153	0.360	0.116	0.320	0.164	0.370	0.104	0.306
medical	0.162	0.368	0.087	0.282	0.200	0.400	0.122	0.327	0.197	0.398	0.156	0.364
gross	0.386	0.487	0.182	0.386	0.411	0.492	0.473	0.499	0.442	0.497	0.408	0.492
net	0.073	0.261	0.324	0.468	0.066	0.249	0.020	0.140	0.047	0.212	0.123	0.329
modified	0.318	0.466	0.209	0.407	0.268	0.443	0.103	0.303	0.099	0.299	0.243	0.429
triple_net	0.187	0.390	0.238	0.426	0.183	0.387	0.359	0.480	0.364	0.481	0.165	0.372
stars	2.575	0.771	2.482	0.650	2.650	0.807	2.672	0.738	2.770	0.790	2.370	0.661
stories	3.129	4.824	2.917	1.954	2.743	4.379	3.928	5.208	5.000	7.867	2.762	3.831
neightent7	16.704	4.066	15.018	4.024	16.192	5.496	17.343	6.071	17.715	4.549	18.872	3.575
fipsunemp	6.926	0.979	5.654	0.996	6.346	0.394	5.687	0.518	5.148	0.244	6.422	1.099
medicare_expend	405.192	209.597	1118.999	495.222	482.075	252.355	273.537	75.785	2551.379	1087.296	643.716	401.943
constate	1.000	0.000	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

In this two-panel table the mean, standard deviation and sample size is segmented across the 12 MSAs included in this analysis. A review of the data indicates a number of similarities across the MSAs (the Star rating by CoStar), as well as some stark, and important, differences (hospital quality ratings)

comparing between properties in a state with or without CON legislation.¹³ For the total sample, MOB properties command a 17.0% premium over POB. MOB properties in states without CON command an 8.4% premium over POB properties, while in the states under CON constraints the premium exceeds 23.8%. This difference in the premium indicates a potential market distortion as a result of CON policy that limits capital responses (to potential market conditions) and forms the basis for including the *constate* variable in the analysis.¹⁴

Table 3 breaks this relationship down by MSA. For each MSA the first line is the sample of POB space offerings and the mean annual base rent per square foot for that subset. The second line presents the MOB subsample. Italicized and bolded MSAs are located in CON states. With the exception of the Denver sample, the average MOB base rent is higher than the POB rent. For the others, the premium varies from 1% for Orlando to 17% for Minneapolis. These are means and do not include any controls for other factors that influence the base rent. For the empirical tests we investigate the determinants of office rents by regressing the quoted asking rent per square foot, on explanatory variables that describe the location, typical leasing provisions and physical characteristics of the facility along with the quality and proximity measures for the nearest hospital.

Empirics

Base rent offerings are assumed to be given in the independent standard forms as follows:

$$\log y = X_f b_f + \varepsilon_f \quad (6)$$

where y represents the natural log of the rent per square foot, and X is a vector of explanatory variables including building attributes, local economic measures and proximity/quality rating to the nearest hospital. The disturbance ε represents those unobservable characteristics of the pool of properties that affect the base rent, and the errors are assumed to follow a normal distribution with zero mean and variance σ^2 . As the database is comprised of individual office base rent offerings, it is assumed that each observation has a set of unobserved factors, or amenities, such as undisclosed lease terms that contribute to the observed rent. The variables include data specific to the property (e.g. age, generic lease terms (i.e. gross or net), building class, medical office space indicator); data at the county and neighborhood level (e.g. unemployment, Medicare expenditures, hospital location and quality ranking); and data that reflects variations among MSAs (e.g. *constate*).

Given the prior that there is variation between neighborhoods within counties and across MSAs, a least squares model of this structure has limitations for this particular analysis. It is understood that the distribution of observed office space is subject to

¹³ In a test of small sample bias we dropped all those properties in counties with less than four observations and generated the same mean and premium measures. The premiums for the reduced sample are statistically identical to those obtained from the entire dataset.

¹⁴ It should be noted that the variable *constate* will be incorporated into the models interacting with medical with the variable name *conmed*.

Table 3 MSA level sample distribution and mean rents for POB and MOB

MSA	n	Rent	Rent Proportions
<i>Atlanta</i>	2241	14.61	0.86
	432	16.92	1.16
<i>Boston</i>	1515	17.43	0.98
	144	17.83	1.02
<i>Charlotte</i>	869	16.08	0.88
	217	18.28	1.14
Denver	1233	17.61	1.00
	171	17.59	1.00
Houston	936	18.98	0.96
	230	19.78	1.04
Indianapolis	663	14.30	0.90
	123	15.81	1.11
Minneapolis	1053	13.45	0.85
	159	15.76	1.17
<i>Orlando</i>	1048	15.51	0.99
	192	15.70	1.01
<i>Phoenix</i>	1113	17.25	0.93
	382	18.54	1.07
Pittsburgh	537	15.43	0.98
	54	15.74	1.02
<i>Seattle</i>	1060	20.10	0.97
	241	20.77	1.03
Sacramento	1076	18.12	0.95
	322	18.98	1.05

MSAs in bold are bound by state level CON Laws. The first column provides the sample breakdown between POB (top) and MOB (second). The second column is the mean rent again segmented between POB and MOB. The 3rd column provides proportional comparisons between POB and MOB within the MSA. For example, POB rents in Atlanta average 86% of MOB

conditions endogenous to the MSA and the county (within the MSA), such as supply relative to demand in the area, variations in the quality of surrounding properties, and commute times across MSAs. Including location variables in a single level model does not address all the unobserved biases embedded in the economic conditions of the local/regional market. For this reason, we control for unobserved multi-level variations by converting the stylized least squares structure into a hierarchical linear modeling (HLM) or multilevel model. For example, although Pittsburgh, Indianapolis and Minneapolis might be considered similar in terms of socioeconomic characteristics and economic output, they are subject to different MSA-level office market conditions and different state level legislation (e.g. Certificate of Need). Similarly, Fulton County and Clayton County, adjacent to one another in the Atlanta MSA, have per capita incomes of approximately \$37,200 and \$18,900, respectively. These differences

suggest that MSA and county level variables matter, and further that the endogeneity present in the levels is not respected in a single level model.

Hierarchical Linear Modeling (HLM)

While metropolitan and county level indicators can be included in an ad hoc manner, depending on the problem, we borrow an important analytical framework from the education, evaluation, and health care literatures that we have used successfully in other studies. School researchers have long recognized that students learn within groups, nested within classrooms, grades, schools, and school districts. The achievement of students within a particular classroom may be related to the specific teacher, which may be related to attitudes or supervision at a particular school. Bryk and Raudenbush (1992) provide a detailed explanation of the method of multilevel modeling or hierarchical linear modeling (HLM), and Goodman and Thibodeau (1998), as well as Goodman and Smith (2010) provide examples of this method applied to issues in real estate (housing markets and mortgage default, respectively).

We begin with a baseline set of ordinary least squares regressions to serve as a point of comparison and demarcation. Start with the model

$$\ln y_f = a_f + b_f x_f + d_f z_f + \varepsilon_f \quad (7)$$

- f subscripts refer to base rent variables.
- y_f appropriate base rent indicator.
- x_f variables subject to HLM.
- z_f variables not subject to HLM.
- ε_f error term.

An OLS formulation implicitly assumes that the relationships are constant either across counties or across metropolitan areas and that the error variances are also constant.¹⁵ Referring to Eq. (7), assume arbitrarily that constant a_f varies by MSA M and slope b_f varies by county C (counties may or may not be nested within a specific MSA).

Then, write coefficients:

$$a_f = g'_o + g'_M M + \varepsilon'_a \text{ MSA} \quad (8)$$

$$b_f = h'_o + h'_C C + \varepsilon'_b \text{ County} \quad (9)$$

where ε'_a is the error term in the constant substitution and ε'_b is the error term in the slope substitution.

¹⁵ The HLM approach is selected based on the documentation presented above and also on the fact that the chi-square test confirmed a statistically significant improvement in explanatory power over OLS. All results from the models that follow are available in OLS upon request.

Substituting (8) and (9) into (7).

$$y_f = g'_o + g'_M M + h'_o x_f + h'_C C x_f + d_f z_f + [\varepsilon_f + \varepsilon'_a + \varepsilon'_b x_f] \quad (10)$$

One could assume alternatively that constant a_f varies by county (which again may or may not be nested within a single MSA) and slope b_f varies by MSA. The substitution and algebra are similar and are omitted for brevity.

Estimating the HLM model (10) with errors $\varepsilon' = \varepsilon_f + \varepsilon'_a + \varepsilon'_b x_f$ requires maximum likelihood methods. While adding MSA and county dummy variables controls for *fixed* effects, HLM represents a *random* effects model, where the MSA and county impacts are modeled explicitly. HLM, as a form of generalized least squares modeling, treats controls for the non-distance, non-quality, aspects of the rent regression, so that we can address various forms of the distance and quality relationships directly.¹⁶

HLM Results

The HLM approach is utilized throughout to allow for random effects from the county and MSA factors. In Table 4 a buildup approach is employed with a set of initial base models followed by models incorporating the fixed building effects and then the random location controls. Model (a) presents a log- log relationship between the base rent and the distance from the nearest hospital. The coefficient is negative and significant and suggests a doubling in distance will result in a 5% reduction in base rents. Although the value of the coefficient will change as other variables are added, the negative relationship between distance and rent will be consistent throughout the analysis. Model (b) is a log-level model with the distance (in 1000s of meters) and distance squared incorporated as explanatory variables. Both explanatory variables are significant at 99% and together the variables tell us that rents fall as we move away from the hospital, but the rate of fall decreases the further from the hospital; this is similar to the log-log form in Model (a). That should not be surprising as the observations are in urban areas so there are other market influences in the vicinity of the office diluting the influence from the hospital beyond the single medical facility.

In Model (c) log distance is included along with a set of dummy variables representing the quality rank for the nearest hospital. The negative relationship with distance remains stable and the quality variables behave as expected, the higher the rank the higher the rent. For example, doubling the distance to the nearest hospital (from 1 to 2 km) reduces the mean asking rent (\$16.80) by almost 5% to \$15.99. The binary hospital quality coefficients have substantive impacts; nearness to a hospital of quality 5 increases the rent by $\exp^{0.152084}$ or approximately 16.4%, compared to a hospital of quality 1.

Looking more closely at distance, if the nearest hospital is closer to the town center than the MOB, the distance coefficient in Model (c) could simply be measuring the urban rent gradient. To test this, Models (d), (e), (f), and (g) include the distance to (and quality of) the second nearest hospital (noted in this discussion as hospital 2). Model (d) incorporates the second nearest hospital. Both facilities present proximity impacts. The

¹⁶ The following models are available as ordinary least squares regressions on request.

Table 4 Build-up Models

Fixed	Dependent Variable: lrent						
	(a)	(b)	(c)	(d)	(e)	(f)	(g)
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
lndist1	-0.0468 ***		-0.0484 ***	-0.0281 ***	-0.0287 ***	-0.02609 ***	-0.02560 ***
distance		-0.0129 ***					
distancesqrd		0.0002 ***					
ov1dum2			0.0466 **				
ov1dum3			0.0543 ***				
ov1dum4			0.1131 ***				
ov1dum5			0.1521 ***				
lndist2				-0.0552 ***	-0.0677 ***	-0.04446 ***	0.04203 ***
o1ver45					0.0932 ***	0.05992 ***	0.05484 ***
o2ver45					0.0467 ***	0.03270 ***	0.02768 ***
class_b						0.07427 ***	0.07425 ***
class_a						0.20222 ***	0.19843 ***
medical						0.11367 ***	0.09220 ***
gross						0.12120 ***	0.11912 ***
triple_net						-0.08836 ***	0.08704 ***
stars						0.07846 ***	0.07644 ***
stories						0.00481 ***	0.00424 ***
age						-0.00503 ***	-0.00503 ***
age2						0.00003 ***	0.00003 ***
neighrent7							0.00210 ***
fipsunemp							0.02299 *

Table 4 (continued)

Dependent Variable: lnrent									
Random	medicare_expend								0.00013 ***
	conmed								0.05960 ***
	constant	3.0117 ***	2.6906 ***	2.9482 ***	3.3728 ***	3.4374 ***	3.05706 ***	3.08588 ***	
	Log Likelihood	-5698.85 ***	-5753.79 ***	-4981.55 ***	-5625.53 ***	-4819.25 ***	-2485.31 ***	-2397.03 ***	
		SD	SD	SD	SD	SD	SD	SD	
	MSA constant	0.1054	0.1027	0.1133	0.0919	0.1005	0.09852	0.07362	
	county constant	0.1887	0.1912	0.3267	0.1740	0.1758	0.14588	0.12703	
	neighrent7							0.00561	
	fipsunemp							0.00000	
	medicare_expend							0.00009	
	conmed							0.05219	

This table presents the results from a series of build-up multilevel models with the log of rent *logrent* serving as the dependent variable. The objective with this set of models is to confirm that a relationship exists between the base rent and the two key variables of distance from a health facility and the quality rating or service reputation of that health facility. *** = 99%, ** = 95% and * = 90%

inclusion of the second facility resulted in a significant reduction in the value of the coefficient for the variable representing the distance from the first hospital. This is likely a result of the combined effect from facilities that are proximate to one another. For example, it is frequently the case that in suburban medical complexes there will be multiple high-level health facilities such as outpatient surgery, a traditional hospital, and a research hospital in the same “neighborhood.”

In Model (e) the distance measures for the first and second hospital are retained with the addition of a dichotomous measure for the ratings of both. As previously mentioned there is little discernable difference between a rating of 4 or 5 and, coupled with the potential for collinearity in the more complex models we transformed the categorical quality ranks into a dichotomous variable coded 1 if the facility is rated 4 or 5 else 0. The coefficients for the distance variables are reasonably consistent with those from Model (d). The additional quality variables perform as expected; in both cases the positive sign indicates that hospitals with higher quality ratings have a positive influence on rents of proximate MOB. For example, if the nearest hospital has a grade of 4 or 5, office proximate office space will have a 10% rent premium (coefficient of 0.0932), and the coefficient for the second facility indicates a 5% premium (coefficient of 0.0467). With all five derivations of the base test of distance decay and quality spillover yielding supportive results the next two models are expanded to include the fixed property and random location effects.

Model (f) incorporates the property-specific fixed effects and this set of controls generally perform as expected. Class A and B properties have higher base rents than do Class C. The coefficient sign for gross rent is positive and the sign for triple-net is negative.¹⁷ CoStar’s “star” rating is positive, suggesting higher rated properties command higher rents. Similarly, the variable *stories* indicates taller buildings have higher rents. The coefficients for *age* and *age*² indicate that as the buildings age the rent they command falls, but it falls at a decreasing rate with age – in other words the buildings depreciate at a decreasing rate. This is consistent with findings reported in Fisher et al. (2005). As expected, properties identified as appropriate for medical use also command a premium, in this case around 11% across the sample. The distance and quality variables maintain sign and significance with the inclusion of the property controls. The distance variable for the nearest hospital is virtually unchanged in magnitude, while there is some reduction in total impact from the quality variables and the distance from the second hospital.

Model (g) includes both property and location attributes and provides a good summation to this point. All of the property attributes are significant, in predictable ways. Medical properties (*medical*) rent for about 9.7% more than non-medical properties. As previously observed older properties rent for less, and the rate of deterioration decreases with age. Distance matters, although the coefficient (−0.026094) is about half as large as in Model (c). The distance coefficient of hospital 2 (−0.0420) is close to twice as large as the nearest hospital (−0.0256), and both are significant. This suggests that in many cases the office observations are in suburban areas and the second nearest hospital may be closer to the city center. Still another potential explanation is the confounding influences of multiple hospitals in the vicinity of the office. The central business district of Atlanta, for example, has five hospitals within a three-mile radius.

¹⁷ Gross and triple net are compared to a combined variable representing net and modified.

Such proximity could create a number of conflicts in the results, especially when the proximate hospitals have varying quality ratings.

At the county/MSA level the coefficients for *neighrent7* and *medicare_expend* are significant at 95% or above. The coefficient for *neighrent7* (mean rent for 7 nearest neighbors), included to control for observations located in higher or lower rent markets, is positive. The Medicare variable represents the total dollars of Medicare expenditures by county for 2015. The Medicare coefficient indicates that the base rent (*logrent*) is higher in counties with higher levels of expenditures. The insignificant coefficient for the county level unemployment rate is the outlier, and this inconsistency will prevail in subsequent model tests. The CON variable *conmed* (interaction coded 1 if the office is identified as MOB and located in a CON state) is materially significant even when controlling for the medical office premium.¹⁸

As an application of the findings from Model (g) assume there are two offices located in a market where the base rent estimate is \$20.00 for a property located adjacent to a hospital. Further, assume that space A is located 1 km from both the nearest and second nearest hospital with quality rating of 2 and space B is essentially right between the two facilities (i.e. adjacent). Holding all other variables constant at their mean except our distance variables there is a reduction of \$1.34 (\$0.50 or 2.5% for the nearest and \$0.84 or 4.2% for the second) in the base rent to \$18.66 for space A relative to space B.

Consider another example where the two offices are adjacent to two different hospitals, but space C is next to a hospital with rank 2 and space D is the same distance from a rank 4 hospital (we only consider the nearest hospital in this scenario). In this example, the base rent is nearly 6% higher when proximate to the higher quality hospital. Recall, also, that the premiums for the neighborhood, the medical designation and the medical designation within a Certificate of Need State are already addressed in controls. What is clear from the Table 4 models is that quality of the hospital and proximity to that hospital are important in determining the rent premiums that potential tenants are willing to pay.

In Table 5 the models are designed to isolate the relationship between the key variables (distance and quality) and rents for observations identified specifically as MOB properties. In Model (h) the attention is on MOB distance. Model (i) is a closer examination of the relationship between MOB rents and the quality rating. Model (j) includes both distance and quality for the first and second nearest hospital, again, centering on MOB rents. The coefficient estimates and significance of the property and location controls in all three models are generally consistent with those from Table 4 (g), allowing us to focus on the distance and quality coefficients.

In Model 5 (h) the distance variable is converted into a series of distance bands at 1000-m (e.g. band 1 = 0–1000, etc.) increments with distance band 5 representing all observations greater than 4000 m from the hospital. The distance bands are interacted with the medical variable to allow for focusing on the link between the hospital and MOBs specifically. The coefficient for distance remains negative, but is now extremely small as the explanatory power is transferred to the distance band interactions. The

¹⁸ As previously noted this is consistent with prior research (Goodman & Smith, 2020) that confirms there is a premium in medical specific space for properties located in a Certificate of Need State. The premium is an artifact of the distortions in space supply resulting from CON policies.

Table 5 Important Interactions

		Dependent Variable: lnrent			
		n=16.011	h	i	j
		Variable	Coefficient	Coefficient	Coefficient
Fixed	dist11000		−0.00445 ***	−0.00497 ***	−0.00619 ***
	dist21000				−0.00236 ***
	distband2med		−0.05692 ***		
	distband3med		−0.10623 ***		
	distband4med		−0.08615 ***		
	distband5med		−0.05634 ***		
	dist11000_med			−0.01422 ***	
	d1listsqr1000med			0.00094 ***	
	ov1dum2			0.01911	
	ov1dum3			0.03682 **	
	ov1dum4			0.09322 ***	
	ov1dum5			0.09527 ***	
	o1ver45		0.06738 ***		
	over45_dist		−5.66E-09 ***	−5.54E-09 ***	
	over45_med				0.02659 **
	o2ver45_med				0.02826 **
	class_b		0.07645 ***	0.07715 ***	0.07667 ***
	class_a		0.19895 ***	0.19894 ***	0.20240 ***
	medical		0.15473 ***	0.13145 ***	0.07683 ***
	gross		0.12096 ***	0.12032 ***	0.12077 ***
	triple_net		−0.08838 ***	−0.08817 ***	−0.08780 ***
	stars		0.07886 ***	0.07888 ***	0.07885 ***
	stories		0.00550 ***	0.00558 ***	0.00486 ***
	age		−0.00460 ***	−0.00462 ***	−0.00475 ***
	age2		0.00003 ***	0.00003 ***	0.00003 ***
	neighrent7		0.00213 ***	0.00215 **	0.00220 **
	fipsunemp		−0.02589 ***	−0.02411 *	−0.02670 **
	medicare_expend		0.00015 ***	0.00015 ***	0.00012 **
	conmed		0.05042 ***	0.05291 ***	0.06534 ***
	constant		2.51967 ***	2.47897 ***	2.60125 ***
	Log Likelihood		−2484.68 ***	−2488.16 ***	−2454.36 ***
			SD	SD	SD
Random	MSA constant		0.07857	0.07527	0.07714
	county constant		0.12662	0.12950	0.11978
	neighrent7		0.00590	0.00586	0.00594
	fipsunemp		0.00000	0.00000	0.00000
	medicare_expend		0.00010	0.00010	0.00009
	conmed		0.04806	0.04836	0.05458

This table presents the results from a multilevel model with the dependent variables *logrent* and includes a number of interaction variables. The interactions serve two important roles. First, interacting distance and quality provides insight into their joint influence on rents. Second, the identifier variable for medical is interacted with quality and distance to isolate the influences on MOB specific rents. *** = 99%, ** = 95% and * = 90%

distance band interactions (i.e. *distband2-5med*) have significant, negative coefficients. However, the coefficient values are concave and indicate a peak impact at 2000 to 3000 m from the hospital, followed by a decrease in influence.

One potential explanation for this relationship is that the sample of MOB properties falls rapidly with increasing distance. Over 52% of the MOB observations in the dataset are within 4000 m of the hospital. Another potential explanation points to the previously discussed evolution of the healthcare industry at large. As healthcare professionals move out to retail spaces and position their practices and services closer to the potential market, the rents paid for MOB space will be influenced by markets outside of traditional office space parameters. The dichotomous rating variable for the nearest hospital (*olver45*) indicates a nearly 7% premium for the higher ranked hospitals. We include an additional interaction between the dichotomous rating variable and distance (*over45_dist*). The negative (and significant) impact for the variable *over45_dist* suggests that the rent gradient for high quality hospitals is steeper than for lower quality hospitals. Thus, MOBs near high ranked hospitals have a higher base rent and that rent deteriorates at a faster rate when compared to lower ranked facilities. Consistent with the two independent measures of distance and quality, the interaction variable provides similar support for the distance/quality decay in office rents, suggesting that the rate of decay is higher for higher ranked facilities. This relationship is enhanced with a significantly larger rate of reduction in base rent for the medical interaction models. Finally, the variable *conmed* is the interaction between the dichotomous variable identifying a property in a Certificate of Need state (*constate*) and the MOB designation (*medical*). The coefficient suggests medical properties in CON states command a 5% premium in excess of the of the 17% premium that the medical coefficient suggests.

In Model (i) the focus shifts from the distance to the hospital rating along with interactions between distance and medical. Recall, the hospital rating is a categorical variable coded 1 through 5. For Model (i) that variable is converted into a series of dummy variables with the base at the lowest rating – 1. According to the coefficients there is no significant difference in proximate office rents between hospitals rated 1 or 2. Significant differences from rank 1 begin at a rating of 3 (95%) and continue through 5. Note also, that the rent premium is upward sloping through the rating scale. As one progresses from 1 to 3 and 3 to 4 the rent premium increases. Base rents near hospitals with a rating of 4 or 5 are expected to be 10% higher compared to those rank of 1 or 2. The coefficient estimates for the interaction between distance and the medical designation (*dist11000_med* and *d1listsqr1000med*) are both statistically significant and consistent with the findings in Model (h). As distance from the hospital increases, the base rate decreases, but at a decreasing rate.

In the last model, Model (j), the dichotomous ranking for the nearest and second nearest hospital is interacted with the medical indicator and included along with the distance for the first and second nearest hospitals. The coefficients for the rating and medical interaction indicate that MOB rent premiums are around 3% for both the first and second hospitals. The distance variables indicate that MOB rents fall approximately 6% for every 1000 m from the nearest hospital and 2.5% for each 1000 m from the second nearest hospital. In summary, both proximity to the two nearest hospitals and the quality of those hospitals is influential in the rental rates for proximate MOBs.

It is difficult to choose among regressions (h), (i), and (j), because these Table 5 regressions are *not* nested versions of each other, nor of the Table 4 regressions, and non-nested tests among them (*J* tests, as performed by Goodman & Thibodeau, 2003) are likely to be inconclusive. Nonetheless, the Table 5 regressions, as well as those in Table 4, provide a consistent story. Distance matters, quality matters, and they matter together.

Conclusion

Institutional investor interest in the MOB segment has grown profoundly over the last decade, but as yet there has been little academic work on this important property segment. Our results strongly support the theory that proximity to a health facility enhances base rent. Further, the reputation of the health facility as represented by the overall ranking provides a significant and material impact on the rent tenants are willing to pay. This research provides an academic introduction to the MOB market, confirms that there are rent drivers embedded in the MOB market that are unique to this segment, and provides one of the first connections between the real estate and the health services literatures. The findings represent the first study on capitalization of quality and distance on rents in the health care market. The health services literature (Folland et al., 2018) has paid literally no attention to the important cost of office space, treating it as fixed, or not treating it at all. We have subjected our estimates to numerous sensitivity tests and they appear robust to various specifications. The estimates indicate both statistically and materially significant relationships between rents and the characteristics of area hospitals (distance and quality rating or reputation).

Only in the last decade have analysts recognized that MOBs represent a distinct market with different tenant markets and a different set of factors that influence marketability. This has been, in part driven by the relatively stable returns provided by MOBs, coupled with the growth in the market as an outgrowth of increased demand for healthcare. As the United States continues to grapple with the tough decision of how to provide quality healthcare to the population at a sustainable cost, public policies that provide greater access are likely to perpetuate the growth in the MOB market into the foreseeable future. In this article, we have identified a relationship between office space rents and proximity to health facilities. Moreover, this positive relationship between health facility proximity and rents (or rent premiums) is enhanced by the reputation of the facility. For those tenants that provide health services, a high-quality reputation is an amenity that can spill over into their enterprise. Reputation is capitalized into the rent that tenants are willing to pay for proximity to and affiliation with, a higher quality facility.

Our findings should be of interest to investors who seek opportunities to increase margins through rents and or expenses. The results should also inform researchers examining spillover effects from agglomeration and those engaged in office market research. The groundwork laid by this paper, and Goodman and Smith (2020), provides a foundation for additional analysis in the MOB market. One potentially fruitful dimension would be an examination of the transaction market. Looking at the variations in cap rates, or similar measures, between traditional professional office buildings with the MOB assets may provide further important insights into the market structure of this important sector.

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